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An agent-based model for lighting technology adoption in the residential sector: integration of social, technological and economic factors

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Resumo

CHAMORRO ERAZO, Jairo Daniel. **Modelo baseado em agentes para o estudo da difusão de tecnologias de iluminação no setor residencial: integração de fatores sociais, tecnológicos e econômicos.** 2016. 45 f. Dissertação (Mestrado em Ciências) – Escola de Artes, Ciências e Humanidades, Universidade de São Paulo, São Paulo, 2016.

A implementação de políticas públicas orientadas a incentivar a adopção de tecnologias de iluminação mais eficientes no setor residencial precisa de ferramentas analíticas capazes de descrever assertivamente as condições de mercado necessárias para uma penetração exitosa destas inovações. Este documento descreve, utilizando modelagem baseado em agentes, a relação entre os micro comportamentos dos usuários ao adoptar as tecnologias de iluminação e as macro tendências agregadas de difusão no setor residencial brasileiro. O modelo também estuda a dinâmica existente entre a relação dos parâmetros das redes de interação e as caraterísticas emergentes no processo de difusão em diferentes cenários econômicos para os custos energéticos e tecnológicos.

Palavras-chaves: Modelagem baseado em agentes. Redes Complexas. Previsão tecnologica. Tecnologias de ilumincação. Energia. Difusão de inovação.

Abstract

CHAMORRRO ERAZO, Jairo Daniel. **An agent-based model for lighting technology adoption in the residential sector: integration of social, technological and economic factors** 2016. 45 p. Dissertation (Master of Science) – School of Arts, Sciences and Humanities, University of São Paulo, São Paulo, 2016.

The implementation of energy policies oriented to incentive the adoption of efficient lighting technologies in the residential sector requires of analytic tools able to describe the market conditions necessary for a successful penetration of the innovations. This article describes, using an agent-based model, the relationship between the micro behaviors of householder's adoption of lighting technologies and the aggregated macro patterns of diffusion in the Brazilian residential sector. The model also studies the dynamic between the interaction network parameters and the emerging diffusion characteristics in different economic scenarios for energy and technologic prices.

Keywords: Agent-based modeling. Complex networks. Technology forecasting. Lighting technologies. Energy. Innovation's difussion.

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1 Introduction

The implementation of different initiatives, like energy efficiency policies or substitution programs, oriented to encourage the adoption of energy efficient technologies in the residential sector requires the integration of an adequate set of analytic tools able to describe the market conditions necessary for a successful introduction and penetration of the innovations (TRAN, 2012).

However, there is not an individual energy-economy model able to offer solutions to all the questions raised during the design, implementation and monitoring of these sort of initiatives (MUNDACA et al., 2010). Therefore, it is required integrated methodology portfolios able to describe the mechanisms by which the innovations spread throughout the market.

Currently these portfolios still require complementary research tools for studying the performance of these programs in complex contexts, where characteristics like asymmetric information, imperfect competition, strategic interaction, collective learning and multiple equilibria criteria are included (TESFATSION, 2003; CHEN, 2012; DAWID; FAGIOLO, 2008).

The research of technology diffusion has been traditionally developed over economic highly stylized and analytically tractable models (DAWID; FAGIOLO, 2008; TESFATSION, 2006). Classic tools, like the macro-level Bass model, use predictive equations based on the relationship between the likelihood of innovation's adoption and the number of previous adopters (BASS, 2004). However, these methodologies present great limitations when they intend to include the complex interactions among structural attributes, institutional arrangements and behavioral dispositions (DAWID; FAGIOLO, 2008; TESFATSION, 2003).

The agent-based modeling (ABM) is a bottom-up approach for simulation currently broadly used in such diverse fields of research as marketing, biology, logistics and communication systems (BOCCARA, 2010; NICOLIS; NICOLIS, 2012). In the field of economics, terms like Agent-based Computational Economics (ACE) has emerged from extensive discussions about the benefits of this approach, mainly because the AMB's ability to capture the relationship between heterogeneous structures of individuals and the emerging pattern derived from their interaction (DAWID; FAGIOLO, 2008; TESFATSION, 2003; JUDD, 2006). These properties provide great potential to the ACE in the analysis of adoption and technological change (DAWID, 2006)

The micro-level agent-based modeling of technology adoption captures the individual perception about the utility of adopting the innovation and the social interaction among the consumers. Therefore, the aggregation of different micro-models configurations originates the emergent patterns of technology diffusion (LACIANA; ROVERE; PODESTA, 2013), central ideia in explanatory models, such as the "consumer diffusion paradigm" proposed by Gatignon and Robertson (GATIGNON; ROBERTSON, 1985).

The agents choose a decision strategy based on environmental conditions and internal state variables. Thus, the variations on these attributes create heterogeneity in the individual behaviors. Many studies point out that the typical S-shaped diffusion curves is originated by the intrinsic heterogeneities among individuals during the adoption (LACIANA; ROVERE; PODESTA, 2013). This disaggregated technique is especially useful for assessing how the decision process can be influenced by social network characteristics (PERES, 2014).

This document develops an agent-based model for studying the influence of individual behavior and network properties in the adoption and diffusion process of tree different lighting technologies in the Brazilian residential sector (incandescent, compact fluorescent and LED), between 2005 and 2030. Within the model the prices of energy and technology acquisition changes exogenously over the time, providing different economic scenarios. The results descrive the relationship between the parameters of the micro-models and the emerging macro patterns of technology difussion.

The document is organized as follows: the next section presents a general description of the innovation systems from a complex systems perspective, followed by a deeper analysis of the elements used for modeling the consumer's behavior in the ABM. Chapter 4 analyses the market and technology conditions and describe the economic scenarios for the prospective simulation. Chapter 5 presents the agent-based model characteristics. Finally, a presentation and discussion of the results and further directions.

2 Diffusion of innovations in a complex systems perspective

2.1 Review of traditional methodologies for modeling diffusion

Traditionally, the research of innovation's diffusion focus on the description of the market penetration during the early stage of its life cycle (CHANDRASEKARAN; TELLIS, 2007). For characterizing this process, we will use the same life cycle description by Golder and Tellis (TELLIS; GOLDER; FOSTER, 2004):

1. Commercialization is the date a new product is first sold.
2. Takeoff is the first dramatic and sustained increase in a new product's sales.
3. Introduction is the period from a new product's commercialization until its takeoff.
4. Slowdown is the beginning of a period of level, slowly increasing, or temporarily decreasing product sales after takeoff.
5. Growth is the period from a new product's takeoff until its slowdown.
6. Maturity is the period from a product's slowdown until sales begin a steady decline.

The research on this field has described significant regularities over empirical findings. Probably the most relevant of them is the shape of the diffusion curve, which over numerous studies plots a cumulative sales of new products over time as a S-shaped curve (COHEN; HO; MATSUO, 2000).

Various studies have identified many drivers of the diffusion process. Nevertheless, the main models used nowadays still have problems for describing important parts of the process, like the takeoff and slowdown, or even show lake of capacity for including relevant information as network topologies for representing patterns of information spreading (CHANDRASEKARAN; TELLIS, 2007).

Probably, the most used tool for describing innovation's difusssion is the Bass Model (BASS, 2004). It has long been the platform of research in marketing because of its simplicity and good predictive ability. This model uses a concept similar to the spread of diseases through population, the basic assumption is that the adoption of a new product spreads primarily due to the contact with prior adopters. Therefore, the probability of an agent to purchase for the first time is a linear function of the number of previous buyers (CHANDRASEKARAN; TELLIS, 2007).

$$Y(t) = m\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \tag{1}$$

This model uses three key parameters for describing the cumulative adoption over time Y(t): the coefficient of innovation or external influence (p), the coefficient of imitation or internal influence (q), and the market potential (m) (BASS, 2004).

These parameters are quite useful for a good interpretation of the model, Bass interprets the coefficient p as the coefficient of innovation because it reflects the spontaneous rate of adoption in the population. He interprets q as the coefficient of imitation because it reflects the effect of prior cumulative adopters on adoption (CHANDRASEKARAN; TELLIS, 2007). Other researchers interpret p as the external influence referring to the influence of mass-media communications and q as internal influence referring to the influence of interpersonal communication from prior adopters (MAHAJAN; MULLER; SRIVASTAVA, 1990).

However, as it is pointed out by (CHANDRASEKARAN; TELLIS, 2007), the nonlinear estimation of static models such as the Bass model leads to downward biases in parameter values of market potential and the coefficient of innovation and an upward bias in the coefficient of imitation (BULTE; LILIEN, 1997).

Additionally, the Bass model presents other several limitations, probably the main of them is that the model needs data at both turning points (takeoff prior to growth and slowdown prior to maturity) to provide stable estimations and meaningful forecasts (CHANDRASEKARAN; TELLIS, 2007). However, by the time those events occur, the predictive value of the Bass model is limited. Moreover, small changes in the observations leads to big changes on the parameters, which creates instability in the forecasting (BEMMAOR; LEE, 2002; CHANDRASEKARAN; TELLIS, 2007).

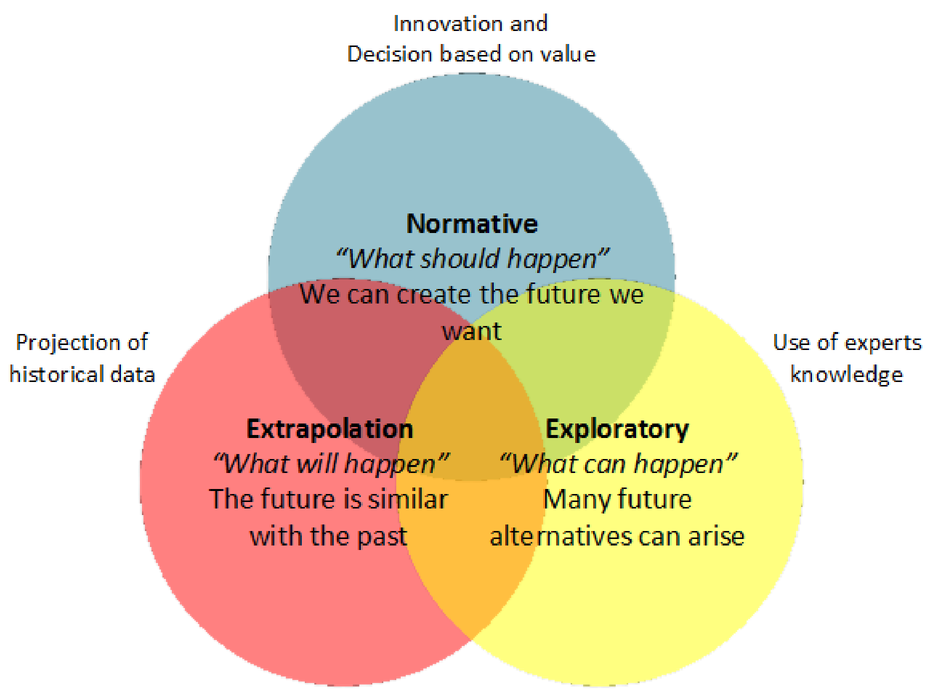
The Bass model does not include the direct influence of any marketing variable as price or advertising neither. The definition of the product within the Bass model is static. Therefore, it assumes that the product does not change over time (CHANDRASEKARAN; TELLIS, 2007).

In this order of ideas, we pretend to use the capacity of the agent-based modeling for representing heterogeneous interactions in order to address these points in a disaggregate level.

2.2 Systems modeling approach: TDS and Complex Networks

Traditionally, the main methodologies used for technology prospection relay in three complementary perspectives (PORTER et al., 2011). (I) An extrapolative methodology that, using the data about the past tendencies of the technology performance, stablishes descriptive parameters about the future. (II) A normative methodology that analyses the social and political context that shape the options for the technology development and (III) the exploratory methodology that allows a deeper analysis about the many future alternatives that could arise (see Figure 1).

Figure 1 – The main complementary strategies for developing a prospective approach of technology innovation.

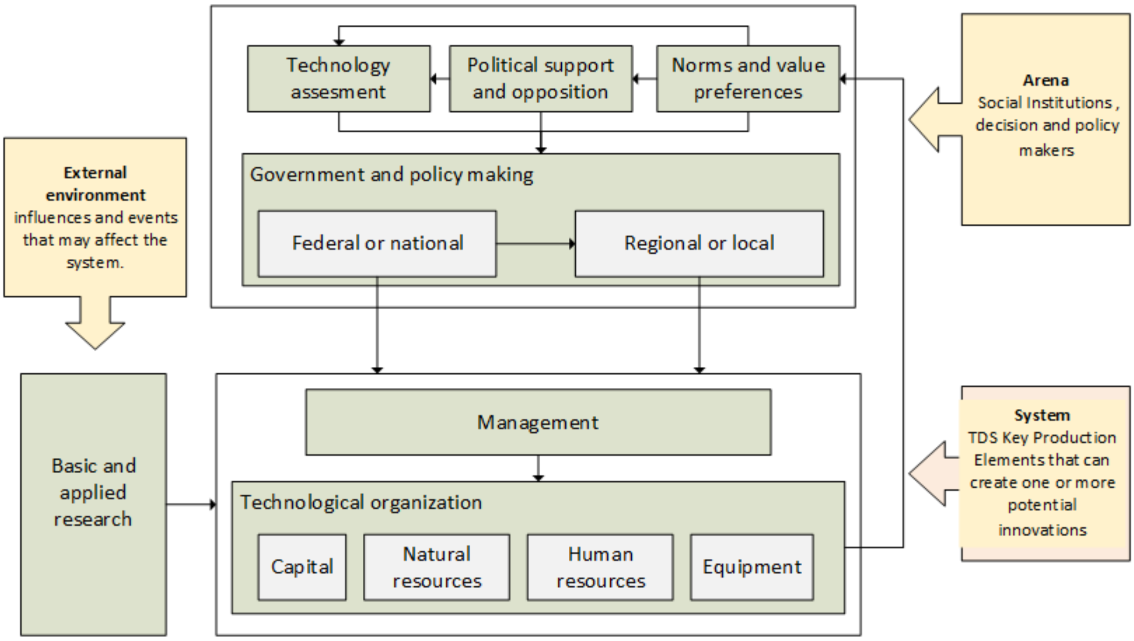


Considering the concept of Technology Delivery System (TDS) to analyse the social interactions that lead to technology development (PORTER et al., 2011), it is possible to represent the innovation's dynamic in a system perspective using four main elements, (1) inputs of the system, such as capital, natural resources, knowledge and human value, (2) public and private institutions that play roles like policy making or technology development, (3) processes by which institutions interact and (4) the outcomes, including both direct and indirect effects on the social and physical environment.

The TDS structure changes over time reflecting the dynamic of the interactions that participate in the technology development. Thus, the mapping of this system provides a clear description of the main actors in the innovation lifecycle and its participation over time.

All these structures could be grouped in three main categories (PORTER et al., 2011; SAGE; ARMSTRONG, 2000), (I) the system, that represents the productive elements that may produce a single innovation or a range of potential innovations, (II) the arena, which contains the social, political and other decision-making entities and (III) the external environment, the events that can affect the system (see Figure 2).

Figure 2 – Technology delivery system (TDS) model for a governmental system, describing (I)the system, (II) the arena and (III) the external environment



Source: (PORTER et al., 2011)

Using this system approach, each one of these categories could be modeled using different sorts of conceptual, statistical and computational tools; for a later integration, which in this document will be developed over a network representation. For example, in relation to the system of economic agents that develop the innovations, the TDS perspective allows to map the essential components of each company that bring to market advances in R&D, identifying the institutions and key individuals that can affect the technological development or be affected by it (PORTER et al., 2011).

A network integration approach offers interesting tools for exploring and analyzing the interaction between social agents (individuals, companies, government, etc.) and the technological, environmental and economical context (BOCCARA, 2010). One of the main characteristics of this network representation is the capacity to capture the micro-level behavior of the systems in terms of individual interactions, which provides constraints and reduce the degrees of freedom of the system (FRENKEN, 2001; LACIANA; ROVERE; PODESTA, 2013). Consequently, the macro-level properties appear as a result of the individual interactions, emerging patterns of auto-organization derived from the individual relationships.

In this example, within the companies that originate the innovations, the collective knowledge is used to achieve the firm's productive objectives (PORTER et al., 2011; FRENKEN, 2001). The process of knowledge creation in the firm is based on division of labor and coordination. Many individuals, department etc. of the firm contribute to the creation of new knowledge, the production of the resultant knowledge necessarily involves the coordination of all these activities (FRENKEN, 2001). On this perspective it is clear that the organizational structure of a firm have an impact on the innovation process, which could be described in a network perspective too.

In this sense, the question is how the characteristic of the network can be understood from a bottom-up perspective, and how we can work backwards from an existing network structure to infer the parameters of individual actions or the conditions under which such actions will occur (FRENKEN, 2001). This network must incorporate the most relevant agents that shaped the knowledge dynamics.

The model developed in this document focus on the representation of the dynamic over the market arena, where the innovation outcomes interact with the customer behavior and external factors as policies and economic conditions. In next chapter, it is described the consumer behavior model used for representing this interaction.

3 Agent's behavior model and network topology

Environmental behavior refers to people actions related to the natural environment, such as the use of resources or space. Behaviors like production and consumption belong to this definition (MOORE, 1979). The dynamic within this behavior could be described as a cyclical process, where micro-level behaviors of many individuals and the macro-level outcomes mutually affect each other. The micro-level behaviors try to satisfy personal needs here and now, characteristic quite related to the common dilemma underlying many environmental degradation problems (JAGER, 2000; MOORE, 1979).

Therefore, the aggregated behavior of all individuals can affect in long term the natural environmental qualities and the human environment, which refers to the technical environment, the economy, the cultural environment and the institutions (JAGER, 2000). Thus, the macro-level driving factors refer to the natural and human environment people live in, which strongly determine the behavioral option they have.

In this context, the cognitive process refers to the strategies a person may employ to determine which behavior to perform in order to satisfy his needs, this strategy belongs to micro-level context. At the micro-level the basic driving forces of behavior refer to human needs and values, behavioral opportunities, consumer abilities and consumer uncertainty (JAGER, 2000; SOPHA; KLöCKNER; HERTWICH, 2013; JAGER et al., 1999).

The consume strategy depends directly on the combination of these characteristics. The relationship between the needs and the opportunity of consumption results in a *level of need satisfaction*, which determines the motivations to consume certain opportunities. The relationship between the consumer's abilities and the available opportunities results in the feasibility of consumption, also known as *behavioral control* (JAGER, 2000; SOPHA; KLöCKNER; HERTWICH, 2013; JAGER et al., 1999). Thus, the consumer's level of need satisfaction, behavioral control and uncertainty are the key factors that determine a type of cognitive processing.

When the behavioral control is high, it is relatively easy to use the resources for satisfying the needs. Therefore, the consumers could use them without elaborating strategies or define alternative sources. In the other side, when behavioral control is low the resources will became harder to get, then the consumers will have to elaborate alternative options for satisfying their requirements.

The agent-based model in this paper implements an adaptation of the behavior classification described by Jager (JAGER, 2000; SOPHA; KLöCKNER; HERTWICH, 2013; JAGER et al., 1999). The combination of the behavioral control *(BC)* and the level of need satisfaction *(LNS)* will define the strategies the consumers could use for satisfying their needs (see Table 1) (JAGER, 2000; SOPHA; KLöCKNER; HERTWICH, 2013; JAGER et al., 1999).

In order to set the abreviations we will use in the following descriptions, the model will use a group of N agents (householders), which could use any of the T lighting technologies available in the market. $L_{i,n}$ represents the technology used for the ith agent in the period of time n.

Table 1 – A classification of behavior strategies using the Level of Need Satisfaction (LNS) and Behavioral Control (BC).)

	Automated	**Reasoned**
Individually determined *(certainty, private, individualist cultural perspective, personal needs).*	(I) Repetition	(II) Deliberation
Social determined *(uncertainty, public visibility, egalitarian cultural perspective, social needs).*	(III) Imitation	(IV) Social comparison

Source: (JAGER et al., 1999)

3.1 Repetition

The theory of individual automated behavior applies in situations when the consumers have high levels of need satisfaction and behavioral control. In this situation, the outcome-uncertainty is low, less publicly visible and more individual centered.

In the model, this strategy consists on the substitution of a lamp with other of the same technology, mathematically:

$$L_{i,n+1} = L_{i,n} \tag{2}$$

Because this automated model only applies when there is a small time interval between behavior and external reinforcements (like social conditioning, energy policies or price variations), the long-terms outcomes can only affect behavior through cognitive processing, and will require the inclusion of social and economic factors (JAGER, 2000).

3.2 Deliberation

The individually reasoned behavior applies when the consumers have a relatively low level of need satisfaction and/or behavioral control. Therefore, consumers have to elaborate alternative strategies for satisfying their needs. In this case, the decision is more individually relevant and less publicly visible.

The optimization strategy is mainly developed in three stages: (1) information acquisition, (2) structuring the decision-making problem, (3) evaluating alternative options (opportunities) and making a choice (JAGER, 2000).

In the resources optimization process within the model, the agent analyzes the energetic and non-energetic costs derived from the use of each k type of lighting technology. In this paper we use the life-cycle cost (LCC) in order to calculate this value.

$$LCC_k = C_k + \sum_{n=1}^{VN} E_{k,n} P_n \left(1+d\right)^{-n} + \sum_{n=1}^{VN} CNE_{k,n} \left(1+d\right)^{-n} \tag{3}$$

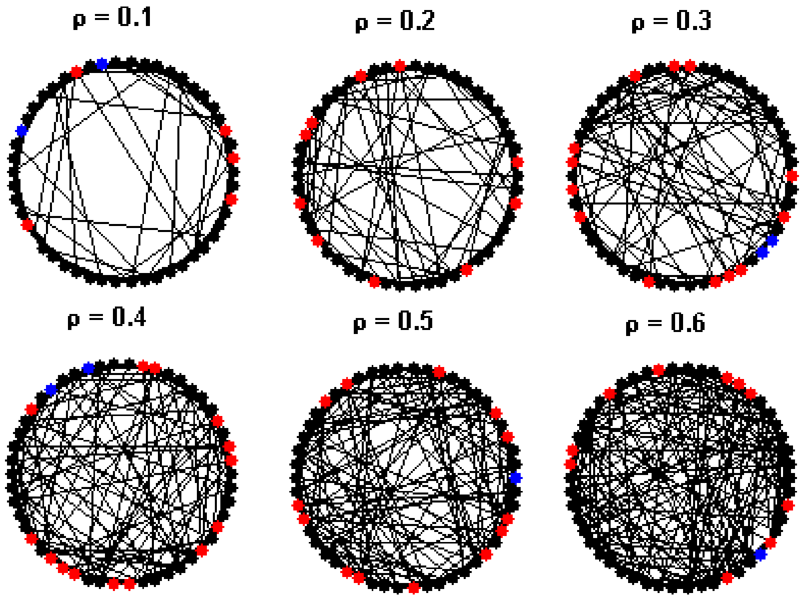
Where C_k is the initial cost for the k type of technology in the initial period of time, $E_{k,n}$ the energy consumed in the period n by the technology k, P_n the energy price for the period n, CNE_n the non-energetic costs in the n period, d the discount rate valid in the n period. It is important to recognize that, because the technologies have different lifetime expectancies among them, in order to compare adequately the LCC we calculate this value for the least common multiple life expectancy of the set of technologies VN.

The energy consumed by technology $E_{k,n}$ changes in relation to the effiency of the technology, which also is variable over time. Because the life expectancy among technology is not the same, the non-energetic cost CNE_n consist on the reposition cost of the lamps over the analysis period.

3.3 Imitation

The theory of socially automated behavior applies mainly when the consumers have relatively high level of need satisfaction and behavioral control. It is mainly used in situations where the resources usage is publicly visible and the needs in question are more

Figure 3 – SW networks generated using the Watts-Strogatz method for 50 nodes with average degree 10 and ρ variable. The node color represents the technology type used by the householder where black (fluorescent), red (incandescent) and blue (LED).



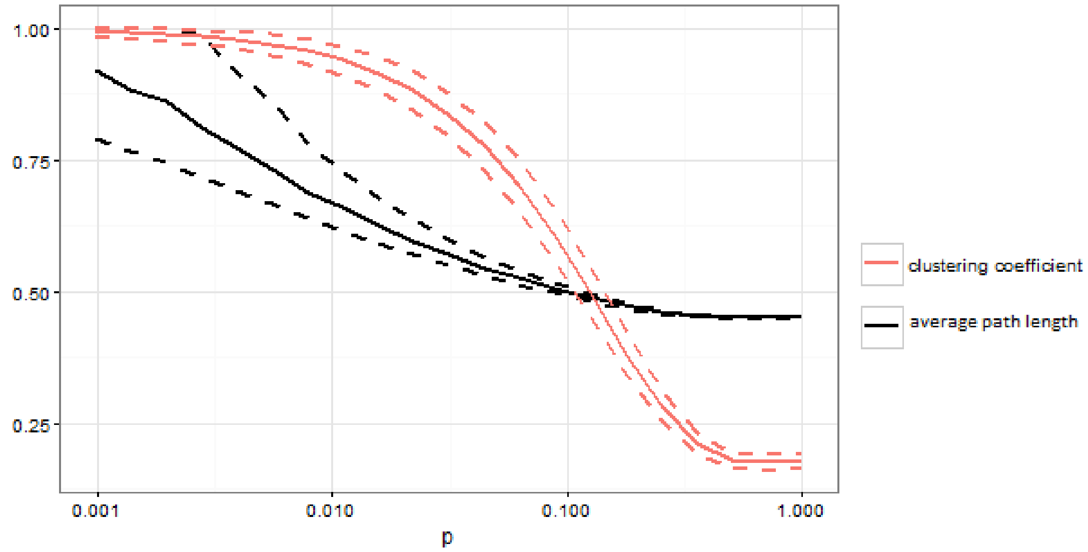
socially relevant (JAGER, 2000). Seeing someone else being reinforced and following his behavior may also affects one's behavior, this process is described in the *Social Learning Theory* (BANDURA; MCCLELLAND, 1977; JAGER, 2000).

Within the modeling of these interactions, different research have used complex networks for representing social dynamics, reducing complex systems to the basic components and their relationships (LÓPEZ; SANJUÁN, 2002; SOPHA; KLöCKNER; HERTWICH, 2013; SOPHA; KLÖCKNER; HERTWICH, 2010). In this context, the communication process would depend on the number of agents interacting and the network topology (LÓPEZ; SANJUÁN, 2002; SOPHA; KLÖCKNER; HERTWICH, 2010).

Research on technology diffusion in the residential sector describe the Small World (SW) topology as the most adequate for representing the information flux between householders, mainly because its characteristics of highly clustered and relative small path length (SOPHA; KLöCKNER; HERTWICH, 2013; SOPHA; KLÖCKNER; HERTWICH, 2010; LACIANA; OTEIZA-AGUIRRE, 2014).

The small world networks are located between regular and random networks (WATTS; STROGATZ, 1998a). To interpolate between regular and random networks, we consider the Watts and Strogatz method (WATTS; STROGATZ, 1998a; WATTS; STROGATZ, 1998b).Starting from a ring lattice with n vertices and k edges per vertex, we rewire each

Figure 4 – Average results of shortest path length and the clustering coefficient for 100 simulations of SW networks, where the dotted lines represents a distribution of the 5th and 95th percentiles of the distribution pf both graph characteristics.



edge at random with probability p (see Figure 3). This construction allows us to 'tune' the graph between regularity (p close to 0) and disorder (p close to 1) (WATTS; STROGATZ, 1998a).

The structural properties of these networks will be evaluated by their characteristic path length $L(p)$ and clustering coefficient $C(p)$. The regular lattice at p close to 0 is a highly clustered, where L grows linearly with the number of nodes. On the other side the random network where p is close to 1 is a poorly clustered, small world where L grows only logarithmically with the number of nodes (WATTS; STROGATZ, 1998a). Figure 4 reveals the broad interval of p over which $L(p)$ is almost as small as in random networks and $C(p)$ closer to random networks.

Thus, within this social strategy the agent will evaluate the technology type of the other householders in its vicinity (linked nodes), replacing the lamp with the most used technology in its influence group. If there is not a dominant technology as result of the evaluation, the agent will use the repetition strategy.

The networks will be classified using the global clustering coefficient $C(p)$ and the characteristic path length $L(p)$, which will be useful for analyzing the relationahip between the characteristics of the SW networks and the technology diffusion process.

3.4 Social comparison

The theory of socially reasoned behavior applies mainly when the consumers have relatively low level of need satisfaction and/or behavioral control. Therefore, consumers have to elaborate alternative strategies for satisfying their needs in more socially relevant conditions.

Within this methodology, the agent evaluates the energetic and non-energetic costs of the technologies used in its influence group. However, the model only has three different alternatives and the result of this strategy will be reduced in most of the situations to the same of the deliberation method. Therefore, this methodology will not be included in the model.

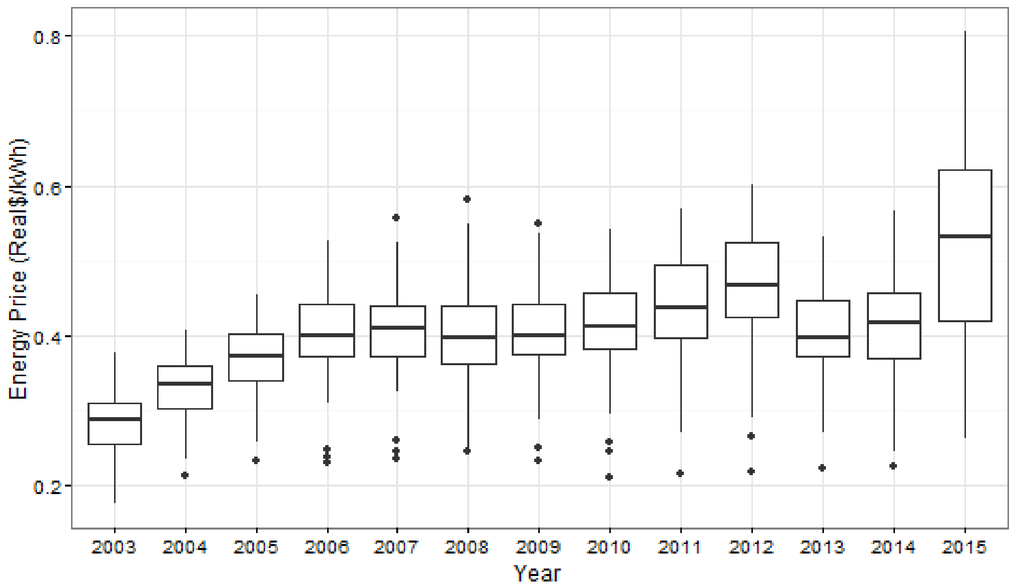
4 Economic context: Energy and technology cost in Brazil

The growing trending of electricity consume in the residential sector, as in other developing economies, has been quite relevant in the planning efforts of the Latin-American governments (YEPEZ-GARCÍA; JOHNSON; ANDRÉS, 2010). The increasing access to goods as coolers and refrigerators has tested the capacity of generation in the region (PROCEL, 2013).

However, many times this planning failed. For example the Brazilian crisis in 2.001 caused blackouts and rationing even in industrial and commercial areas (SOLNIK, 2001). Thus, this situation offered a frame for developing policies oriented to increase the efficiency of lighting services (ROIZENBLATT, 2003). Within this process, many incandescent lamps where substituted for more efficient technologies; over 2.005 almost 50% of the householders used fluorescent technology, mainly compact fluorescent lamps (LFC) (ROIZENBLATT, 2003).

In Brazil, the electricity consumption in the residential sector represents the 24.2% of the total usage (2.013), with an average increment of 2.4% annually since 2004 (ROIZENBLATT, 2003). Recently, Brazil passed through a similar generation crisis, which caused significant increases in the consumer tariffs mainly in 2.015 (see Figure 5).

Figure 5 – Boxplot of the average prices for residential electricity tariffs for kWh in Reais offered for all the energy concessionaries in Brazil from 2.003 to 2.015, with an avarege of 60 concessionaries for 2015. These tariffs do not include aditional taxes as public lighting.

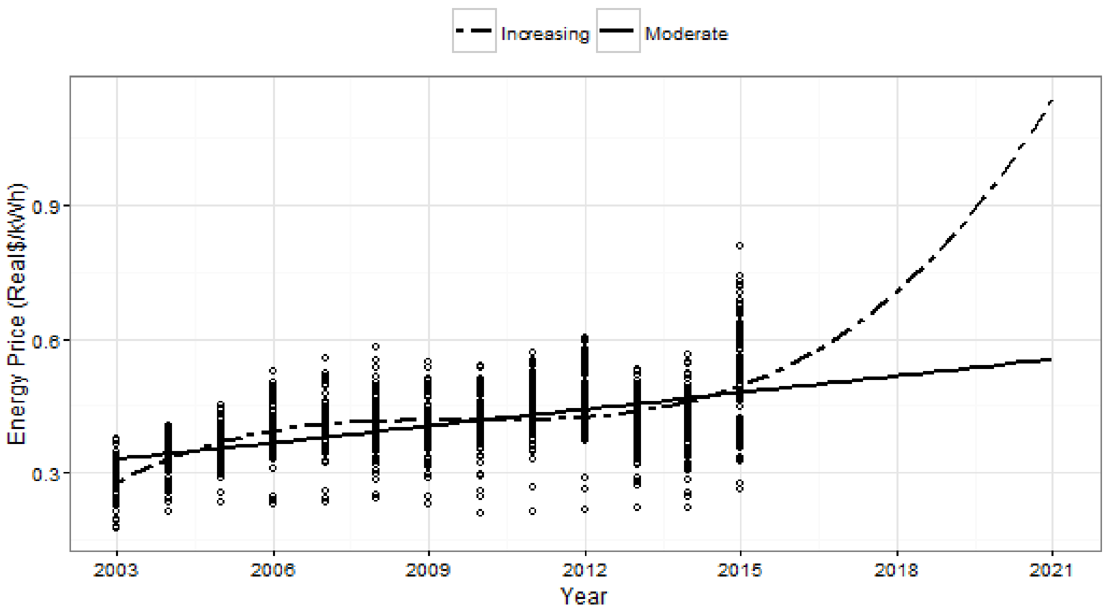


Source: (ANEEL, 2014)

The model will use as reference for the electricity price, the historic information of the average tariffs of the concessionaries for for the residential sector reported by the *Brazilian National Agency of Electric Energy (ANEEL)* (ANEEL, 2014). Aditionally, in order to describe the prices in the future (period of the simulation between 2.016 and 2.030), we fitted two different curves over this information that will represent:

1. Moderate increase: the general tendency of price evolution presented over the historic period of analysis (2.003-2.015) shows small average increments over the years. Therefore, to capture this general behavior it is used a linear regression to model the price evolution over 2.016-2.030, and
2. fast increase: because of the significant price's increments presented over 2.015, and in order to simulate the reaction of the agent-based model over a condition of structural supply crisis, the fast increment forecast is modeled with a 3th degree polynomial (which is able to captured the inflexion presented in the last years).

Figure 6 – Historic information of the average tariffs of the concessionaries for the residential sector B1 reported by the ANEEL over 2.003 to 2.015 and the curves fitted for (I) the moderate increasing trending and (II) fast increasing trending; extrapolated until 2.030.



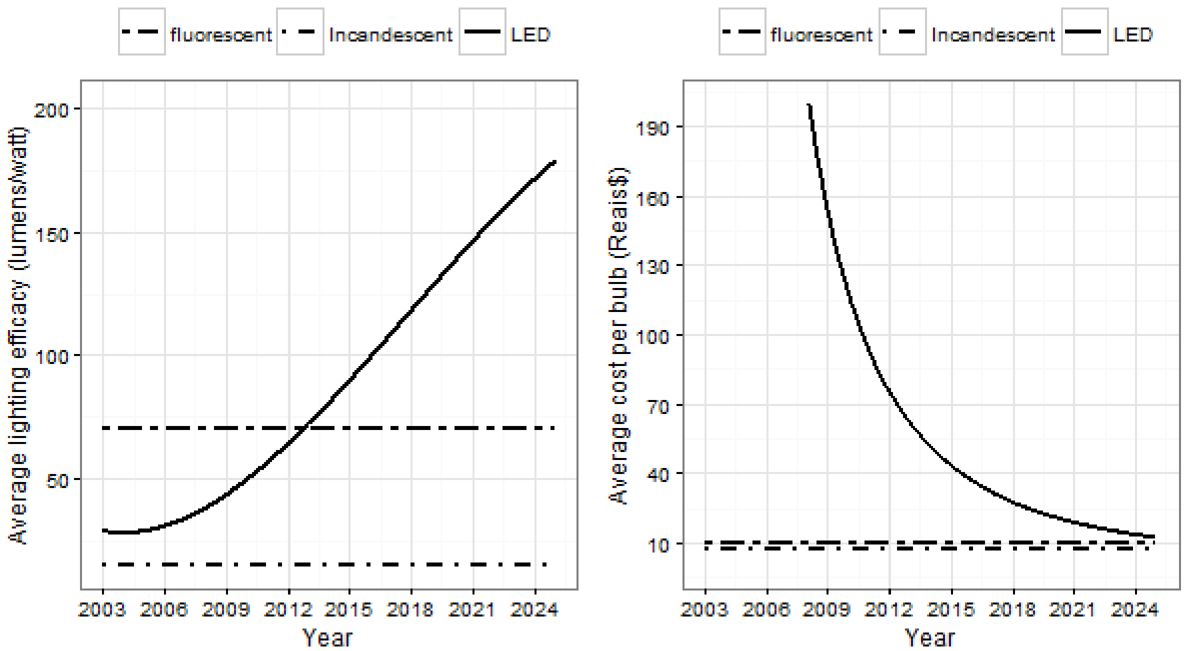
Source: (ANEEL, 2014)

In this way, we have two different scenarios of price evolution that will allow a deeper analysis of the effect of the energy cost in the adoption process. The electricity price is expressed in Reais for kilowatt-hour R$/kWh and does not include aditional charges like public lighting; moreover, we assume a equal relevancy for each concessionary in spite of the differences of size among them.

The initial lamp's technology distribution will be set using the information offered by the *Research of equipment possession and use habits (PPH)* developed in 2.005 for the *National Program in Electric Energy Conservation (Procel)* (PROCEL, 2013). Which estimated that in 2.005 the average lamp possession was the same for incandescent and fluorescent technologies. Consequently, the model will start in 2005 with a technology distribution for the householders of 50% for fluorescent lamps and 50% for incandescent lamps.

In relation to the lamp characteristics, the model will use as an average requeriment for all the lamp's technologies a luminous flux of around 500 lumens (which is the general requirement for regular activities in houses or offices contemplated in the lighting Brazilian policy (TÉCNICAS, 1992)).

Figure 7 – Scenario expected for the change in efficiency and acquisition prices for the different lighting technologies between 2.003 and 2.025.



Source: (EIA, 2014)

Within the abstraction of the model, the most relevant characteristics of the lamp's technologies are the efficiency, which consist in the relation of lumens per watts generated for the lamp (EIA, 2014) and de commercial price. During the period of analysis the incandescent and fluorescent technologies do not show significant variations of these characteristics because they have already achieved technological maturity (EIA, 2014). In the other side, the LED technology is still developing and it is expected significant variations pf commercial price and efficiency (EIA, 2014; WEBB; GRONINGEN, 2015).

Therefore, the characteristics of the incandescent and fluorescent lamps will remain fixed during all the simulation in order to simplify the model, with variation only for the LED technology characteristics. The commercial price of the LED lamps will approach to the acquisition price of fluorescent technology around 2.030 (see Figure 7), scenario based on estimations from the *Annual Energy Outlook 2014* of the *U.S. Energy Information Administration* (EIA, 2014). Additionally, it is expected an increase in the efficiency of around 200 lumens per watt for the same period of time.

5 Description of the agent-based model

Table 2 – State variables in the agent-based model.

Variable	Variable type	Initialization an data group	Units
Adjacency	Static	The adjacency matrix is initialized with the SW network topology using the methodology of Watts-Strogatz, defining the interaction group for the householders.	NxN matrix (where N is the agent's number) with values for (i,j) of 1 when exist a connection between the agents i and j, and 0 otherwise.
Lighting technology	Dynamic	Lighting technology used by the householder: 1. Incandescent 2. Fluorescent 3. LED	Integer number from the group [1,2,3], where each number represents the type of technology in use.
Technology life period	Dynamic	The variable counts the number of periods remaining before the next lamp change.	Integer number of periods (each one representing one month).
Strategy matrix	Static	The matrix defines the distribution of strategy groups: 1. Social householder 2. Conservative householder 3. Rational householder	Integer number from the group [1,2,3] where each number represents the decision profile.

The agent-based model was implemented in Python 3.5, with the objective of offering an analytic tool able to describe the adoption and diffusion process of lighting technologies in the residential sector, exploring this dynamic as a composition of complex interactions, including elements like social networks, imperfect information and heterogeneity in decision taking.

The model is intended to describe the relationship between the interaction network parameters and the emerging diffusion characteristics, in different economic scenarios for energy and technologic prices.

5.1 Entities, state variables and scales

The model is composed by agents that represent users (householders) of lighting technologies. These agents have the same service requirements, a luminous flux around

500 lm and a daily usage period of 6 hours. For simplicity each agent will have only one lamp; therefore, a unique selection process periodically.

The agents' state variables are related to three categories: (1) social structure, (2) information about the technology in use and (3) strategies for technology adoption (see Table 2). These variables could remain static during the simulation or change dynamically in relation to the agent conditions and enviroment context.

The social structure is represented by the adjacency matrix, which is designed using the number of agents N, the average degree m (average number of connections per agent) and the connection probability ρ. These variables will be set as environment variables, which could be modified in order to evaluate the effect of the network characteristics in the diffusion process.

In relation to the strategy selection, the agents have three different heuristic profiles describing the Bayesian probability that the strategy choose (C) uses the repetition strategy (R), the deliberation strategy (D) or the imitation strategy (I) (see Table 3).

Table 3 – Bayesian probability for the householder' profiles for strategy selection, where (R) represent the repetition strategy, (D) the deliberation strategy and (I) the imitation strategy.

Profile	**Strategy's probability**
Social	$P(R\|Social) = 0.3$, $P(D\|Social) = 0.1$, $P(I\|Social) = 0.6$
Conservative	$P(R\|Cons.) = 0.6$, $P(D\|Cons.) = 0.3$, $P(I\|Cons.) = 0.1$
Rational	$P(R\|Rational) = 0.1$, $P(D\|Rational) = 0.6$, $P(I\|Rational) = 0.3$

The model includes these addition environmental variables: electricity price over time, acquisition cost of lighting technologies over time, efficiency of technologies and discount rates. All this information is included exogenously.

5.2 Process overview and scheduling

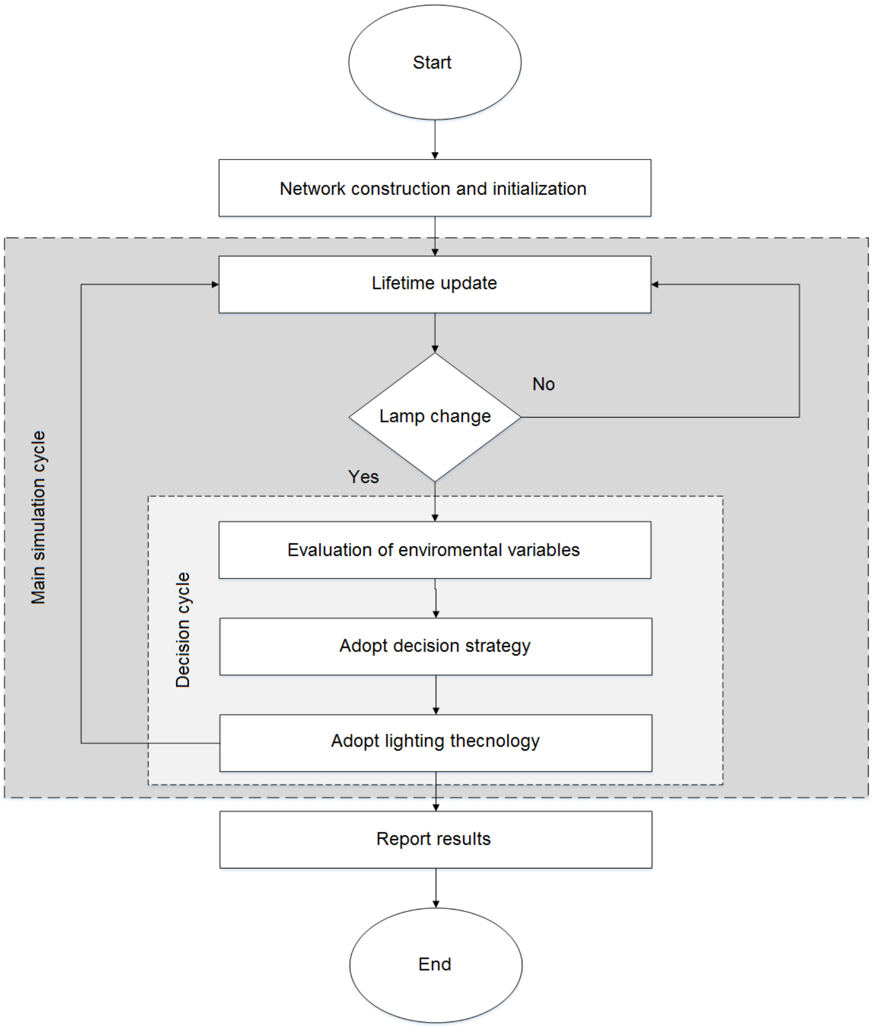
The fisrt stage of the simulation deploys the social structure using the environmental variables as reference. The initialization process assigns a technology type to each agent, which based on the Brazilian researchs is in average 50% incandescent and 50% fluorescent for 2.005. The lamps get a time of availability between zero and the technology's expected life time in order to avoid synchronous changes in groups of the same technology.

In lack of real data about the statistic distribution of the agent's predisposition for adopting any of the behavior strategies in the Brazilian market, this model assigns stochastically the heuristic profiles as follow:

- $P\,(Conversvative|Total) = 0.5$
- $P\,(Social|Total) = 0.3$
- $P\,(Rational|Total) = 0.2$

This distribution is only heuristic and pretends to include behaviors' heterogeneity implementing the notion that the innovative agents are fewer than the followers in most of the markets.

Figure 8 – Flux diagram for the agent-based model.



The model uses discrete steps equivalent to one month of use; therefore, after each cycle the remaining lifetime of lamps is reduced one month synchronously. After the lifetime reduction, the agent evaluates if it is necessary a change of lamp, if it is required the agent recollects the environmental variables and stochastically, in base of its behavior profile, choose an adoption strategy (see Figure 8).

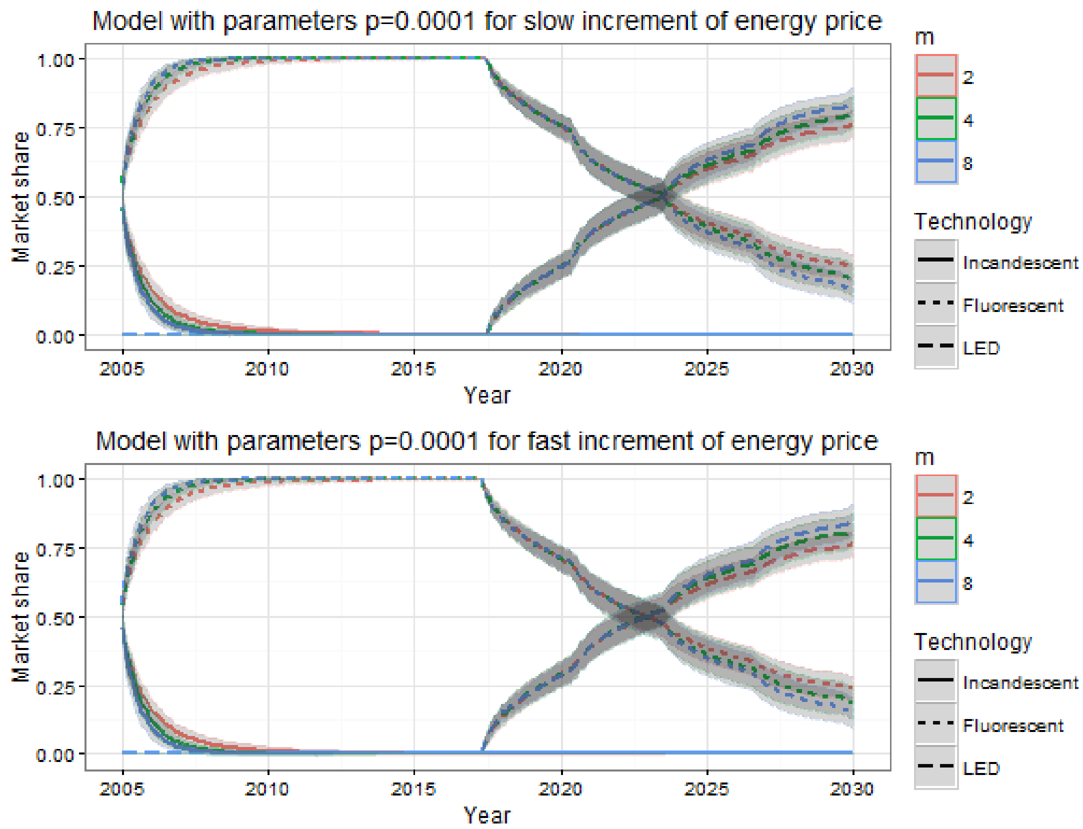
Within this perspective, all the interaction between the agents are held during the imitation strategy. The simulation is developed over a period of 15 years from 2.005 to 2.030.

6 Results

The simulation describe the adoption and diffusion process for lighting technologies in a population of 1.000 agents for two different scenario of electricity price's tendencies: stability and fast increment.

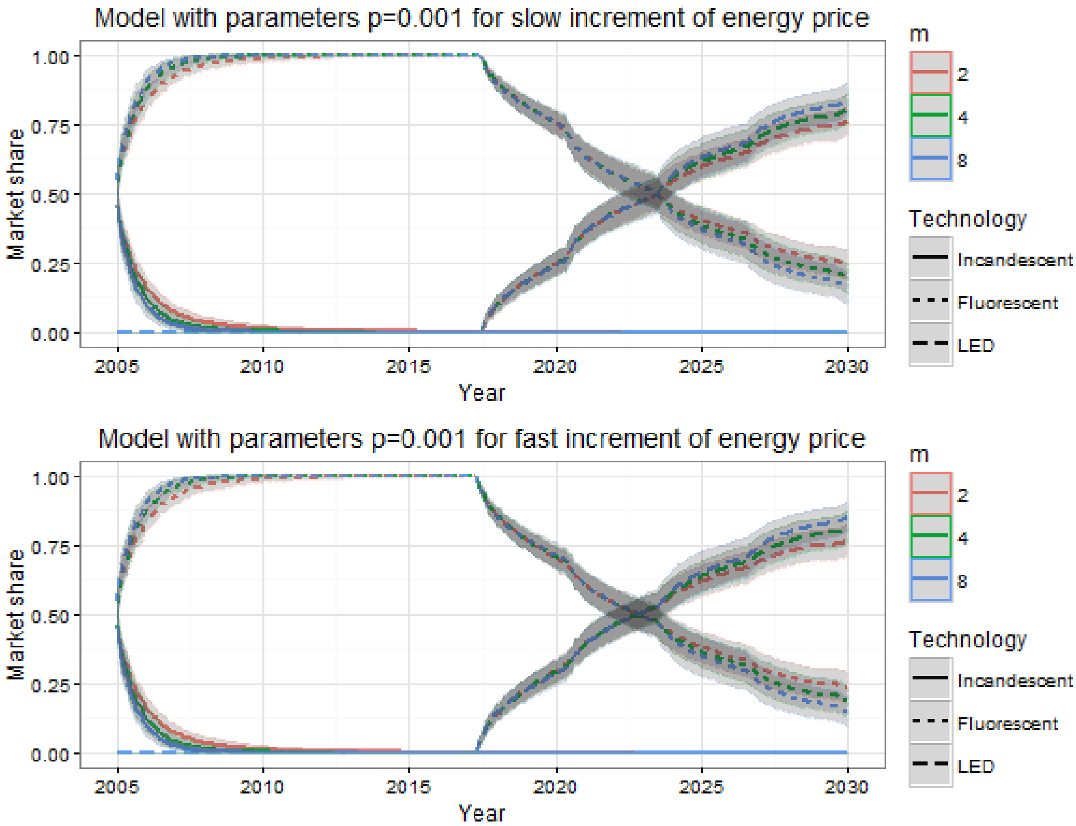
In order to compare the influence of the network characteristics over the difussion process we deploy a simulation for both energy tendencies using as parammeters in the SW network $m = 2, 4, 8$ and $\rho = 0.0001, 0.001, 0.01$. The results are obtained over 100 simulation cycles with annual effective discount rate of 10%.

Figure 9 – Adoption curves for incandescent lamps, fluorescent lamps and LED for the scenarios with stable electricity price (up) and fast increment (down) for a population of $N = 1.000$ with m =2, 4 and 8, and $\rho = 0.0001$.



The tendency graphs represent the usage percent of each type of technology over the entire population of agents through time, where the middle line represents the average value of the simulation's sample and the lateral gray shadow the confidence interval with a distance of 3 times the standard deviation from the central line.

Figure 10 – Adoption curves for incandescent lamps, fluorescent lamps and LED for the scenarios with stable electricity price (up) and fast increment (down) for a population of $N = 1.000$ with m =2, 4 and 8, and $\rho = 0.001$.

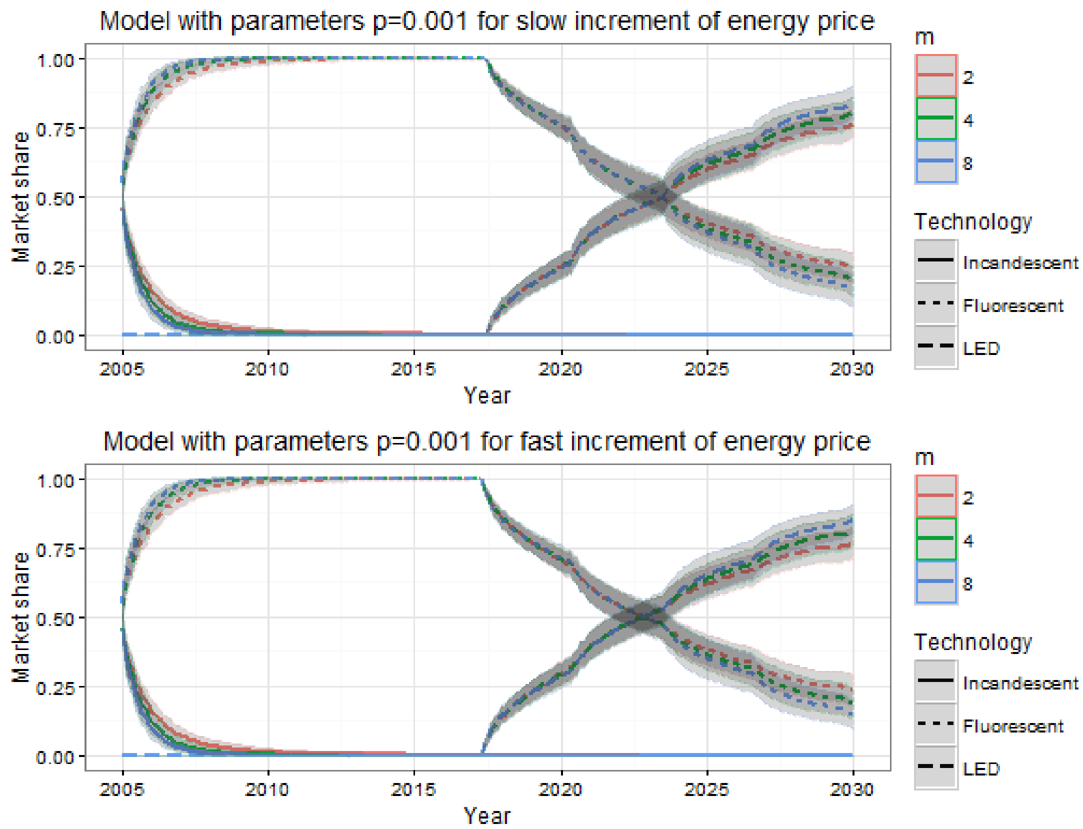


The adoption curves show significant differences with the variation of the average degree of the network over all the values of ρ and even show a stronger influence over the increment slope than the variations of the energy prices. In the initial stage, the fluorescent lamps substitute rapidly the incandescent lamp, sharing the bigger part of the householders' market from 2.010 until 2017, when the LED's adoption process starts, sharing almost 50% of the market around 2.023.

The increment of the average degree fosters the information spread throughout the network, sharing the information obtained for the early adopters with the other householders, mainly with those who uses social strategies for adoption.

The clustering coefficient serves as measure of network's transitivity, that is, the likelihood that if nodes a and b are connected to each other, and nodes b and c are connected to each other, then nodes a and c are also connected. Therefore variations on ρ influence on the effectiveness of the information spread, which could finally affect the characteristics of dispersion over the results.

Figure 11 – Adoption curves for incandescent lamps, fluorescent lamps and LED for the scenarios with stable electricity price (up) and fast increment (down) for a population of $N = 1.000$ with m =2, 4 and 8, and $\rho = 0.01$.

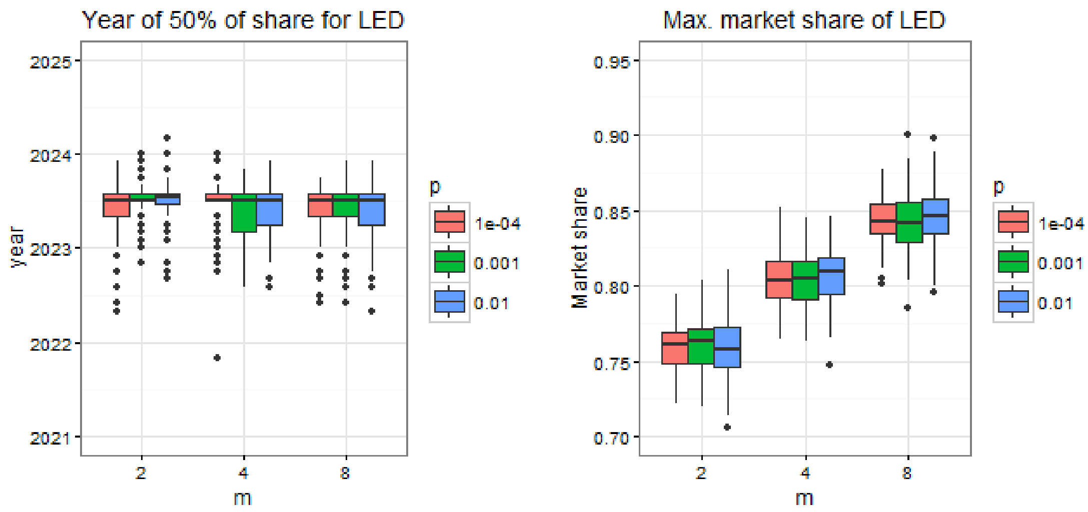


In social networks, the clustering coefficient represents the likelihood that a person in a given network is a friend with the friends of his or her friends. For SW networks, the clustering coefficient could be calculated as $C \sim \frac{3(N-1)}{2(2N-1)}(1-\rho)^3$, where N is the number of nodes (householders) (PERES, 2014). The less clustered scenario have more dispersion in the simulation samples, pattern that appeared as an emergent characteristic of weaker transitivity in social interactions. Thus, more clustered networks affects the individual decision process, making the adoption of new technologies more cohesive among householders, reducing dispersion in the possible scenarios.

The influence of this networks parameters could be analyzed observing the effects they cause over some characteristics of the diffusion curve, the Figure 12 and 13 describes using boxplots the distribution of the year when the LED technology shares 50% of the market and the maximum market share achieved for this technology at the end of simulation for both types of energy price curves.

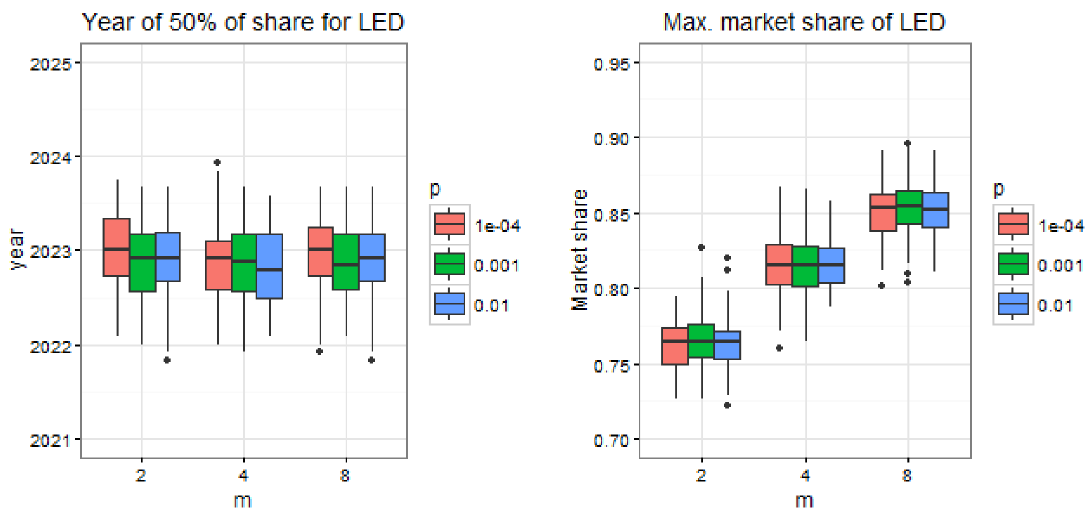
In relation to the 50% year, the case with slow increment of energy price shows small variations over the different network parameters. On the other side, the fast increment of energy price influenced a bigger dispersion. This is an emergent result derived of the pressure created on the early adopters with interest for cost efficiency.

Figure 12 – Evaluation of the diffusion curves' characteristics for LED technology with slow increment of energy price: (left) boxplot with the dispersion of the year where the LED shares half of the total population and (right) boxplot with the maximum share value obtained at the end of the simulation.



The network parameters have more influence in later stages of the adoption process, where the cost efficiency of the LED lamps is evident and the patterns of information flux become more important. In the boxplot with the maximum value achieved of the market share we can see the effect of the average degree. Bigger average degree is related with an easier information flux and better adoption performance.

Figure 13 – Evaluation of the diffusion curves' characteristics for LED technology with fast increment of energy price: (left) boxplot with the dispersion of the year where the LED shares half of the total population and (right) boxplot with the maximum share value obtained at the end of the simulation.



In order to compare the results obtained from agent based model with other tools, we can evaluate the precision in which it could be fitted over S-shape curves obtained with common models.

The Fisher and Pry model (FISHER; PRY, 1971) is quite suitable for this purpose because of its mathematical simplicity. It is based on three assumptions of the diffusion process (FISHER; PRY, 1971): (1) many technological advances can be considered as competitive substitutions of one method of satisfying a need for another, (2) if a substitution has progressed as far as a few percent, it will proceed to completion and (3) the fractional rate of fractional substitution of new for old is proportional to the remaining amount of the old left to be substituted.

The corresponding fraction substituted (named as market share in the document) is given by the relationship:

$$f = \left(\frac{1}{2}\right) tanh\left(\alpha\left(t - t_0\right)\right) \tag{4}$$

Where α is half the annual fractional growth in the early years and t_0 the time at which $f = 1/2$.

An important characteristic of this model is the takeover time, which is defined as the time required to go from $f = 0.1$ to $f = 0.9$ (FISHER; PRY, 1971). This value is inversely proportional to α. In order to set the data for fitting a curve we can transform the market share using this relationship:

$$\frac{f}{(1-f)} = e^{2\alpha(t-t_0)} \tag{5}$$

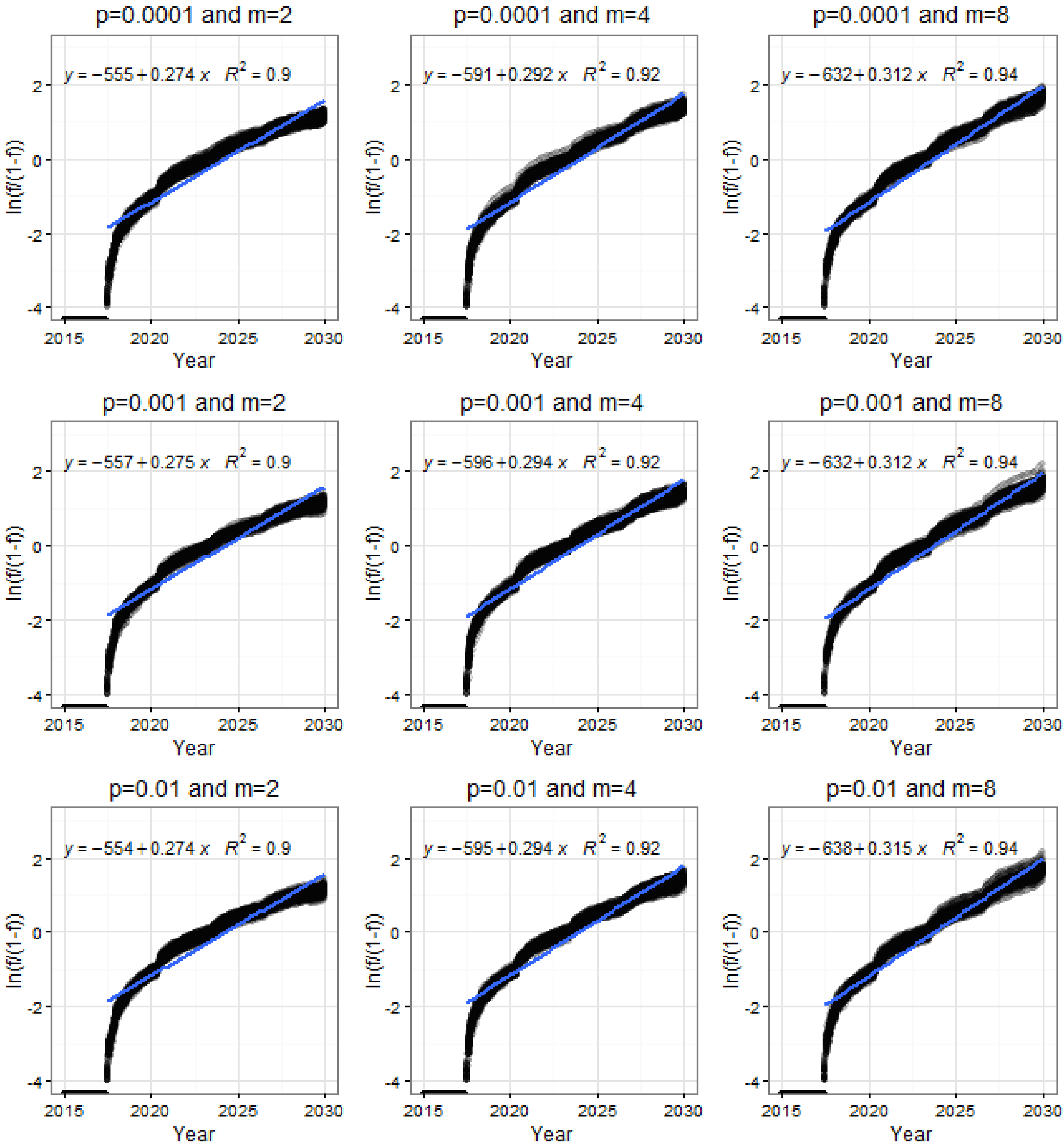
$$ln\left(\frac{f}{(1-f)}\right) = 2\alpha\left(t - t_0\right) \tag{6}$$

Thus, we can calculate over this transformation a linear regression that fits the parameters of the Fisher and Pry curve and test the influence of the network parameters over the model characteristics.

The linear curve fitted will be represented with the equation $ln(f/(1-f)) = ax + b$, where x represents the time, a is equal to with 2α and b is equal to $2\alpha t_0$.

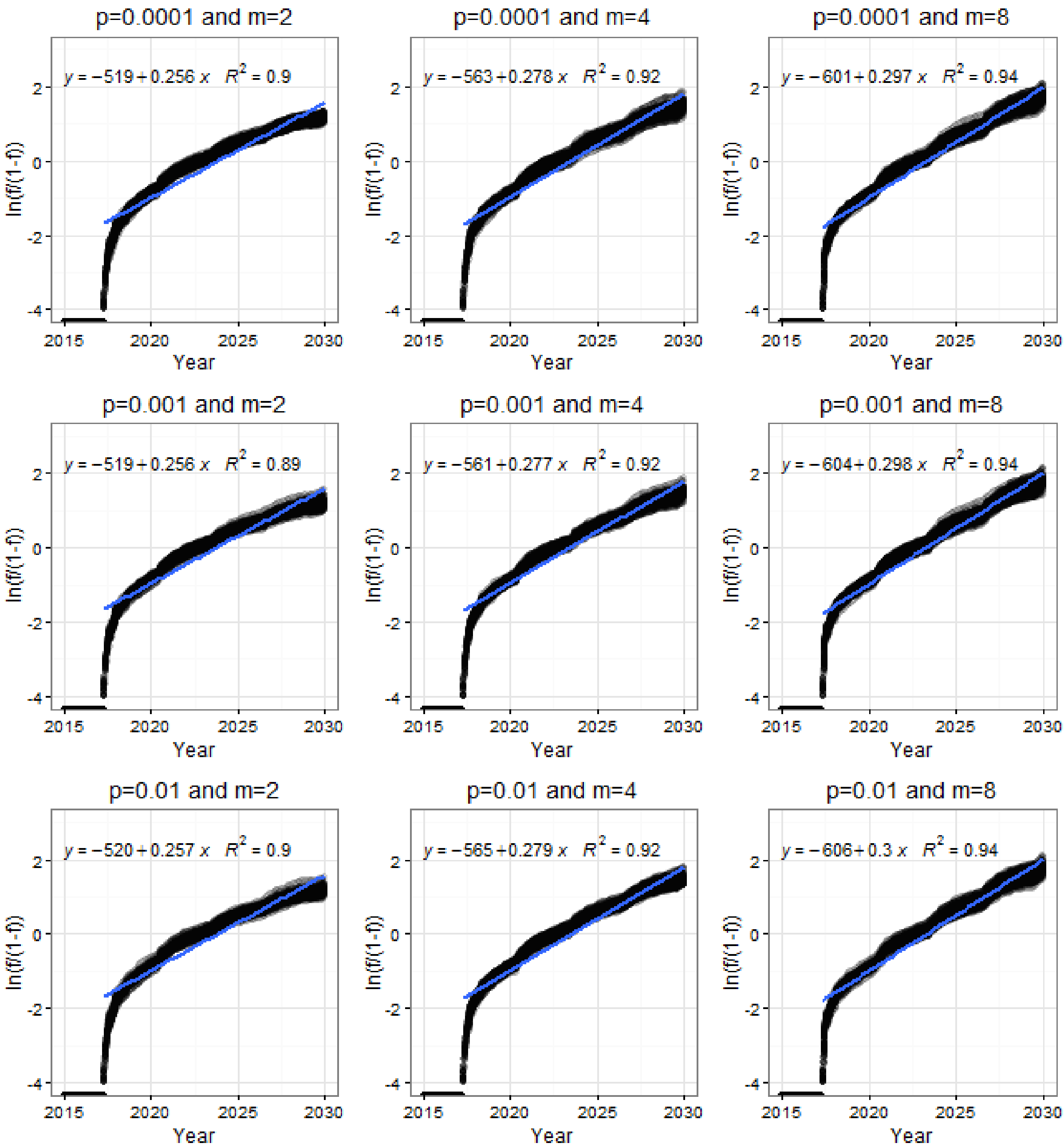
Initially we can see that the main divergences between the simulation data and the Fisher-Pry model happen at the beginning of the adoption process, in this case the agent based model presents a not linear behavior in the transformed space $ln(f/(1-f))$. This emergency is derived mainly from the heterogeneity over agent's behavior.

Figure 14 – Data of the simulation for the LED market share transformed over the relationship $ln(f/(1-f))$ with slow energy price increment for the network parameters $\rho = 0.0001$, 0.001, 0.01 and $m = 2$, 4, 8 and the Fisher and Pry fitted curve respectively.



However, over the main simulation process the data shape is similar to the Fisher-Pry model, we can see additionally that the increment of the average degree of network increases the α value, which reduces the takeover time. It is interesting to see that the increment of α in the fast increment of energy price is smaller than that over the slow increment of energy price. This situation happened because the fast increment of prices pushed the early adopters to start using the LED lamps faster, where the overall prices did not fostered so easily the adoption as in posterior periods of time, creating a longer curve with earlier start time.

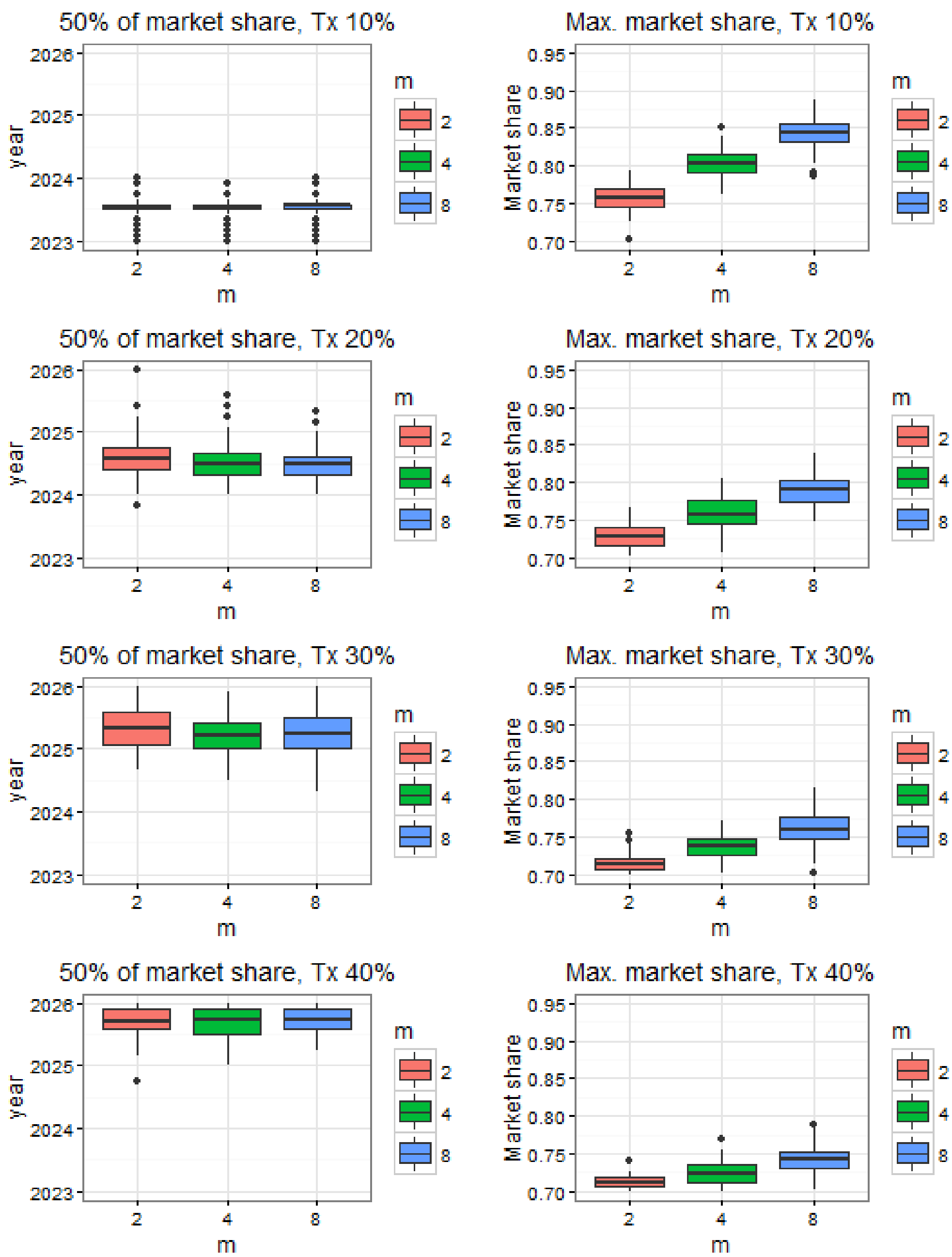
Figure 15 – Data of the simulation for the LED market share transformed over the relationship $ln(f/(1-f))$ with fast energy price increment for the network parameters $\rho = 0.0001$, 0.001, 0.01 and $m = 2$, 4, 8 and the Fisher and Pry fitted curve respectively.



In relation to the t_0, we can see smaller values over the simulation with fast increment of energy price, situation also observed in the boxplot graphs presented before.

A sensitive analysis was deployed too relating changes in the discount rate (which could represents energy policies for subsidize efficient lamps acquisition or other market conditions), the year of 50% of adoption for LED technology and the maximum value achieved of market share at the end of simulation (see Figure 16 and 17).

Figure 16 – Comparison of the effect of the interest rate over the distribution of the year when the LED technology shares 50% of the market (left) and the maximum value of market share achieved at the end of the simulation (right) for the slow increment of energy price. The effective annual interest rates evaluated are 10%, 20%, 30% and 40%



The results shows how the increments in the discount rates makes less economic efficient the LED technology, delaying the adoption process in each of the electricity prices scenarios.

Figure 17 – Comparison of the effect of the interest rate over the distribution of the year when the LED technology shares 50% of the market (left) and the maximum value of market share achieved at the end of the simulation (right) for the fast increment of energy price. The effective annual interest rates evaluated are 10%, 20%, 30% and 40%

7 Conclusions

The Agent Based Modeling (ABM) is a quite useful tool for describing the micro behaviors that creates the macro patterns of technology diffusion. Many researches on this topic have used different mathematical descriptions for the decision process, including relevant aspects about network interaction, heterogonous strategies and dependency to past decision. However, the inclusion of cognitive theories in an integrative fashion and the application of quantitative variables such as Behavioral Control (BC) makes possible the implementation of behavioral rooted models for representing the adoption process.

The agent behavior was divided in four different strategies, three of them used within the model. The strategies was grouped in social and individually determined; including Small World (SW) networks for describing the communication process among householder clusters. The model application used information from the Brazilian residential sector, analyzing the diffusion patterns in three different scenarios of electricity price increment, with different arrangement of network topologies and discount rates (which could represent the impact of energy policies).

The results of the simulation showed that for all the scenarios, the fluorescent lamps substituted quickly the incandescent technology, and the start of the adoption for LED lamps depends strongly on the electricity prices, oscillating between 2.015 and 2.018 for the different scenarios. The inflexion point for the LED technology (defined on the paper as 50% of the total householders) oscillates around 2.023.

Variation on the parameters of the network topology also affects the diffusion process. The increment on the average degree of the network (m) increment the maximum market share achieved by the LED technology at the end of the simulation, emergent behavior related to the effect of m over the imitation strategy.

The reduction of the coefficient of clustering (C), incremented the diffusion of the results, making dizzy the forecasting for the LED's inflexion point. This emergent behavior is related to the transitivity of the network, where highly clustered networks have more transitivity and, through network interactions consolidate faster the adoption process of economic efficient technologies within the householder hubs. These characteristics could be useful for marketing strategies that pretend to consolidate the use of efficient lighting technologies in different social structures.

A sensitive analysis was also deployed for relating changes in the discount rate and the inflexion point delays for LED technologies. As expected the results shows how the increments in the discount rates makes less economic efficient the LED technology, delaying the adoption process, apparently linearly, in the range of analysis. Energy policies makers could evaluate in this way the effectivity of different strategies for fostering the adoption of LED lamps.

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